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Changing opinions on a changing climate: the effects of natural disasters on public perceptions of climate change

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Abstract

The frequency and intensity of natural disasters such as hurricanes, wildfires, and floods are predicted to change as greenhouse gas concentrations increase. These disasters may represent sources of information for individuals as they update their beliefs related to climate change. Using a dataset that includes climate beliefs of respondents, we examine the effect of natural disasters on climate change beliefs and find that hurricanes significantly increase the probability that survey respondents from a given county believe that climate change is occurring and that it is human caused. We find that past experience with certain types of natural disasters (e.g., hurricanes) impacts beliefs regarding whether climate change is occurring and if it is human caused. The research contributes to the literature evaluating climate change attitudes by using spatially disaggregate information on climate change beliefs and exposure to a set of natural disasters over time. Characterizing beliefs and attitudes toward climate change and related policies is important since these beliefs are a determinant of individual adaptation and support for policies related to reducing carbon emissions.

Keywords Climate change · Public beliefs · Natural disasters

JEL codes Q54 · D83 · C33

1 Introduction

Despite the scientific consensus that climate change is occurring and is attributable to anthropogenic causes (Allen et al. 2014; Pachauri et al. 2014), the population of the USA is far from unanimous in their opinions regarding climate change (Leiserowitz et al. 2015).

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Failing to recognize predicted changes in climate can have economically important consequences if it delays individual adaptation or limits support for public policies to correct market failures that lead to excess emissions. Despite overwhelming scientific evidence, the effects of climate change rarely impact the lives of individuals in a salient way and are only observable over long time horizons (Spence et al. 2012; Pahl et al. 2014). One exception to this is with natural disasters, many of which (e.g., hurricanes (Bender et al. 2010), wildfires (Turco et al. 2014), and floods (Bronstert 2003)) are predicted to increase in frequency as a result of climate change. This provides a path through which experience with weather-related events and their frequency may alter individual beliefs about the existence and causes of climate change.

This paper examines how natural disasters affect the percentage of people in a county that believe in, and are concerned about, climate change, as well as attitudes toward specific climate change-related policies. We estimate both the average effect of an additional natural disaster on county-level beliefs, as well as heterogeneous effects based on the historic frequency of the disasters. Importantly, we control for changes in county composition, economic conditions, and political factors that may change with a disaster and over time. To do this, we use results from a set of Yale Climate Communications Project (YCCP) surveys that ask questions related to climate change. We first consider if natural disasters affect opinions about whether climate change is happening. Then, we investigate whether natural disasters affect beliefs about whether climate change is human caused. Finally, we examine if natural disasters affect support for public policies related to climate change, including public research on renewable energy, renewable portfolio standards, and limiting CO_2 emissions from coal-fired power plants. Our study focuses on three types of natural disasters—hurricanes, wildfires, and floods—that are predicted to increase in frequency as a result of climate change (Westerling and Bryant 2008; Bender et al. 2010; Hirabayashi et al. 2013; Mann and Gleick 2015).

This research builds on previous studies that have examined how natural disasters impact public opinions or beliefs related to climate change. Owen et al. (2012) focus on heat waves and droughts, finding that these events increase public support for environmental regulations. Similarly, Spence et al. (2011) find that direct experience with flooding increases concern related to climate change amongst a sample of individuals in England. Our study builds on this work by covering a broad range of disasters and a comprehensive set of survey questions that allow us to examine effects on policy attitudes and climate change beliefs. A recent study by Maas et al. (2020) finds no evidence that gradual changes in precipitation and temperature influence farmer's perceptions about climate change. In contrast to the impacts of gradual changes, our results suggest that hurricanes have statistically significant impacts on climate beliefs and policy attitudes.

Our study contributes to the literature in several important ways. First, whereas most previous work addresses changes in climate opinions at an aggregated state or national level (e.g., Kahn and Kotchen 2011), only a few studies measure changes at a more spatially disaggregated level (e.g., Howe et al. 2015). We model climate change beliefs at the county level across the USA. The more spatially disaggregated unit of observation that we employ allows us to better capture the heterogeneity in changes in climate beliefs due to extreme weather events using panel-data methods. Although it would be ideal to map exposure to specific natural disasters to individual respondents, using county-level disaster impacts enables us to more accurately attribute natural disasters to the people who experience them compared to a state-level analysis. Studies with aggregated national-level or state-level data can confound the impact of weather events with other spatial- and time-varying characteristics that could drive climate beliefs. We also isolate an experience effect

from other channels through which effects could occur, such as news coverage. For example, coastal counties may be less rural than those in the Midwest. Even within a state, urban and rural communities have significant differences in terms of education levels, income, political ideologies, etc. Furthermore, the climate change literature has demonstrated that local adaptation will influence the economic impacts of climate change (Manning et al. 2017), likely influencing beliefs about climate change as well.

Finally, our study is relevant to research in behavioral economics that addresses how information is internalized by individuals. We provide evidence that some natural disasters are internalized as information by the individuals that experience them. Past studies have modeled the response of individuals to exogenous information shocks (e.g., Sims 2003, 2006). Recently, Gibson and Mullins (2020) and Hennighausen and Suter (2020) show that additional information on flood risk, communicated by additional floods, is internalized into property values. Our study builds on this by using survey results that directly measure beliefs and opinions.

The rest of the paper progresses as follows. In the next section, we provide background related to climate change, extreme events, and opinions and beliefs about environmental change. In Sect. 3, we describe our dataset. Section 4 discusses our empirical specification and identification strategy. Finally, Sect. 5 presents and discusses our results and Sect. 6 concludes.

2 Background

The formation of individual beliefs regarding climate change can directly influence public policy. Substantial research has evaluated potential positive and negative feedbacks in the physical environment associated with a changing climate. For example, recent studies (Hurteau et al. 2019) investigate the extent to which wildfires increase or decrease the severity of future fires through an environmental feedback. Kettridge et al. (2010) examine how climate change will affect future cyclone frequency. Previous research also evaluates feedbacks between climate change and human behavior. For example, Davis and Gertler (2015) evaluate how a warming climate impacts adoption of air conditioning systems and leads to further carbon emissions and future climate impacts.

There is an extensive literature on the linkage between climate change and extreme weather events. Early studies on hurricanes (e.g., Emanuel 1987) established a link between the climate and hurricane patterns, and despite later disagreement about the precise impacts (Knutson et al. 2010), more recent work has concluded that climate change increases the frequency of high-intensity hurricanes (Sobel et al. 2016). Climate change has also been linked to changes in drought frequency (Trenberth et al. 2014), as well as an increase in fuel loads responsible for more intense wildfires (Westerling and Bryant 2008). These disasters have dramatic economic and ecological consequences. Pielke et al. (2008) find that between 1900 and 2005, Atlantic hurricanes cost the USA an average of $10 billion annually. As population grows in coastal areas, annual costs will likely increase in the future. Kelly and Goulden (2008) find that climate change results in observable changes to the spatial distributions of plant species, in part due to increased frequency of drought (Le Houérou 1996); however, it is difficult to attribute any one drought event to climate change.

Because of their large, noticeable impacts, several studies have examined the role of natural disasters in changing public opinions on climate change. Examining changes at the national level in the USA, Owen et al. (2012) show that droughts and heatwaves are

correlated with an increase in the probability that individuals support policies that protect the environment. Herrnstadt and Muehlegger (2014) utilize Google Insights data along with voting records to show that abnormal weather is not only associated with an increase in searches related to climate change, but also shifts in congressional voting. By analyzing Google Trends data, Lang and Ryder (2016) show an increase in internet searches related to climate change in areas that have recently been impacted by hurricanes. Bloodhart et al. (2015) examine the role of different information sources in driving perceptions of climate change, focusing on the role of local newscasters. An early study by Diggs (1991) linked drought experiences to farmer perceptions of climate change in the Great Plains region of the USA. Several subsequent studies examine changes in perceptions following flood events in other locations around the world, including Ethiopia (Deressa et al. 2011), England (Dessai and Sims 2010), and Australia (Buys et al. 2012).

Theory from behavioral economics provides an explanation for how individual events can impact beliefs related to global climatic change through a process known as attribute substitution. With attribute substitution, individuals use simple observable outcomes to inform judgements as a substitute for a broader understanding of complex systems (Kahneman and Frederick 2002). For example, Zaval et al. (2014) show that find that individual responses to beliefs related to climate change are influenced in part by their perception of the relative outdoor temperature on the day that they complete the survey. Attribute substitution is related to the availability heuristic (Tversky and Kahneman 1973), wherein individuals put more weight on recent outcomes that are easy to recall for informing their judgements related to the probability of uncertain events. A recent article by Botzen et al. (2021) posits that experiencing climate change risks impacts concern for climate change through the availability heuristic in much the same way that concerns related to the COVID-19 pandemic are influenced by local COVID infection and death rates.

Aside from weather extremes affecting individual perceptions, the literature has shown the importance of economic factors and demographic variables. For example, Kahn and Kotchen (2011) examine how macroeconomic conditions influence public perception of climate change, finding that states with higher unemployment rates experience reductions in the probability that individuals think climate change is happening, and in support for government action to address climate change. Research by Duijndam and van Beukering (2021) finds income per capita and unemployment rates to be important determinates of individual climate change beliefs in European countries. Research by Meyer (2020) finds a similar result for the USA. Additionally, demographics have been shown to have associations with public opinions regarding environmental policies (e.g., Liere and Dunlap 1980; Van Der Linden 2015; Howe et al. 2015). For instance, Van Der Linden (2015) demonstrates that gender influences beliefs that climate change will put an individual's livelihood at risk.

3 Data

To explore the relationship between natural disasters and climate change beliefs, we combine several data sources, including survey data on public opinions regarding climate change, information on natural disasters, and data on county-level economic conditions. In this section, we describe and discuss these data.

3.1 Public opinion data

We employ a dataset of modeled public opinions at the county level that is provided by the Yale Project on Climate Change Communication (Yale PCCC) (2019). The modeled data are based on a collection of separate surveys that were conducted between 2014 and 2019 (Yale PCCC, 2019). The results for each wave of the survey were aggregated to the county level using multilevel regression techniques with post-stratification by the Yale PCCC (Yale PCCC, 2019). The county-level aggregates are validated using several techniques, including comparisons with other surveys.[1] The result is data on public opinions related to climate change for every US county for the years 2014, 2016, 2018, and 2019. One valida- tion technique used by Yale PCCC involves comparing the results of the multilevel regres- sion to independent, state-level surveys conducted over the same period, revealing a mean absolute difference of 2.9 percentage points (Yale PCCC, 2019).

Our empirical analysis uses results from responses to five survey questions from the Yale PCCC—two questions about climate change beliefs and three policy-specific ques- tions. The two belief questions are whether the respondent believes climate change is hap- pening and whether they believe that climate change is caused by anthropogenic actions. Responses to the former question about whether climate change is occurring are binary, and can be answered with either a yes or a no. For the latter, respondents can indicate whether or not they believe (yes, no) climate change is being caused by anthropogenic actions, with individuals indicating "no" having the option to specify it is not caused by humans because they believe it is not happening. We also consider responses to three pol- icy related questions. A "no" answer to "Is Climate Change Human Caused" includes indi- viduals who believe climate change is happening, but believe it is not caused by human activity. Individuals who do not believe climate change is happening are registered as a "no" response for "Is Climate Change Human Caused." Table 1 provides summary statis- tics for county-level averages across time for each of the questions used in the analysis. The specific language for each question can be found in appendix A.1.

There are many factors that contribute to changes in beliefs about climate change. Our study period spans the years 2014 to 2019, and in that time, beliefs regarding whether cli- mate change is happening have shifted. In Fig. 1, we plot the changes in opinion between 2014 and 2019 for two survey questions from the Yale PCCC: (1) Is climate change hap- pening? and (2) Is climate change caused by human activity? Over this time period, the proportion of individuals within a county that believe climate change is happening and that it is human caused, both increased by 1–2 percentage points. However, significant variation in the change occurred with approximately 40.1% of counties reporting a decrease in the belief that climate change is happening and 59.9% of counties experiencing an increase in the belief that climate change is happening.

3.2 Data on natural disasters and demographics

Our analysis includes occurrence data on three different climate change-related natural disasters: hurricanes, wildfires, and floods. We use measures of the annual occurrence of

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[1] Additional details about the methodology used to aggregate the survey results to the county level can be found here: http://climatecommunication.yale.edu/visualizations-data/ycom-us-2018/?est=happening& type=value&geo=county

Table 1 The average percentage of people within a county that answer affirmatively for each of the five questions considered in the study

	2014	2016	2018	2019
Question				
Is climate change happening?	59.10%	64.69%	64.00%	60.20%
St. Dev.[a]	(4.91)	(5.45)	(5.86)	(6.23)
Is climate change human caused?	44.78%	48.05%	51.22	46.92%
St. Dev	(4.38)	(4.80)	(5.03)	(5.24)
Do you support funding renewable?	74.92%	79.86%	82.54%	82.54%
St. Dev	(3.15)	(2.67)	(2.43)	(2.43)
Do you support renewable portfolio standards?	57.42%	61.18%	58.51%	57.39%
St. Dev	(4.28)	(4.38)	(4.29)	(4.51)
Do you support CO2 limits on coal plants?	59.32%	62.61%	62.91%	60.47%
St. Dev	(6.9)6	(7.13)	(6.85)	(6.89)

Note: [a]We report the standard deviation of the report data.
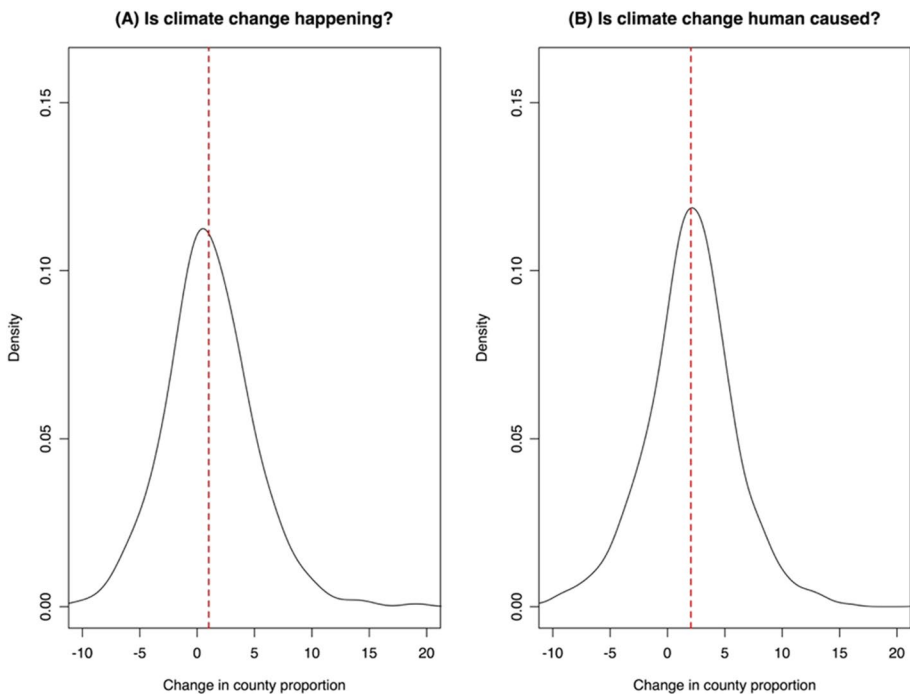
Fig. 1 Distribution of county-level changes between 2014 and 2019 in the proportion of individuals answering affirmatively to two separate survey questions related to climate change beliefs. The dashed line indicates the mean change

these disasters between 2012 and 2019 as well as the historical period preceding 2012, beginning in 1953. A county is considered treated by a given natural disaster if it occurs in the interval prior to a given wave of the survey. Any disasters that occur before 2012 are counted in the historic frequency. The number of disasters that occur within a county in a treatment period is converted to an annual rate.[2] This is done because the treatment periods are not evenly spaced. Disasters that occur within survey periods are counted in the following treatment period (e.g., hurricanes in 2016 are included in the 2018 treatment period). This is done to avoid a situation in which a natural disaster is counted in a treatment period despite occurring after the survey. The historic frequency is calculated in a similar manner, where the number of natural disasters (e.g., hurricanes, floods, or fires) are summed from 1953 through 2012, and then divided by 60, which is the number of years within the historical period. This produces an annual rate of hurricanes, floods, or wildfires within the historical period.

We obtain data on hurricane, wildfires, and flood occurrence through the Federal Emergency Management Administration's (FEMA's) disaster and emergency database, which is in the public domain.[3] The dataset compiles emergency and disaster declarations from 1953 to the present day at the county level (FEMA 2019). The resolution of the data is particularly useful for our analysis because its spatial scale matches that of our survey variables.

Summary statistics for the natural disaster events can be found in Table 2. The statistics reveal that a county in the USA experiences approximately 0.08 hurricanes per year. Flooding events occur within a county on average about 0.1 times per year, and large fire events occur on average 0.03 times per year. Note that in Table 2, all the historic natural disaster rates are lower than the more recently reported numbers. This suggests that, on average, the frequency of these events has increased.

Natural disasters may cause demographic changes that drive county-level changes in opinions about climate change. Hurricanes and wildfires have specifically been found to cause demographic changes (Schultz and Elliott 2013). To isolate the impact of disasters on changes in beliefs and not on the composition of a county, we include county-level annual population from the National Institute of Health's Surveillance, Epidemiology, and End Results (SEER) (NIH, 2019). Severe natural disasters may result in people leaving the affected area, and so including percent changes in population in our analysis helps control for changes in beliefs driven by changes in which people are present. Population and economic variables are averaged across a treatment period.

One way in which a natural disaster may impact beliefs is by first affecting economic factors that then indirectly change beliefs. Previous work (e.g., Kahn and Kotchen 2011) has shown that economic factors such as the unemployment rate influence beliefs in climate change. In order to isolate the direct effects of natural disasters on beliefs, we control for several major economic factors (Kahn and Kotchen 2011). Specifically, we obtain data on per capita income and unemployment at the county level. The median household income data are from the Census Bureau (Census

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[2] The treatment period for 2019 is 2018, the treatment period for 2018 is 2017 and 2016, the treatment period for 2016 is 2015 and 2014, and the treatment period for 2014 is 2013 and 2012. As an additional control for the fact our observations are not evenly spaced, our empirical specification features time controls in the form of year fixed effects.

[3] Data from FEMA can be accessed using the following link:
https://www.fema.gov/data-feeds

Table 2 Summary statistics

Variable	Mean
Natural disasters	
Hurricane rate	0.08
	(0.29)
Fire rate	0.03
	(0.27)
Flood rate	0.10
	(0.36)
Historic hurricane rate	0.06
	(0.08)
Historic fire rate	0.02
	0.06
Historic flood rate	0.04
	(0.05)
Demographic variables	
Population (percent change)	0.46%
	(2.49)
Median household income ($1,000 s)	48.89
	(12.85)
Unemployment rate	5.49%
	(2.62)
2016 Clinton vote share	32%
	(0.16)

Note: The rate variables correspond to the average proportion of counties that experience a natural disaster (e.g. flood, fire) per year. Standard deviations for each variable are reported in parentheses below

Bureau, 2019a) and the unemployment rate data come from the Bureau of Labor Statistics (BLS) (Bureau of Labor Statistics 2019). Table 2 also reports summary statistics for the population and economic variables and shows that counties had an average unemployment rate of 5.49% and an average median household income of $48,000 (2016 USD) over the study period. In addition to economic and demographic variables, political ideology may also influence opinions related to climate change (Dunlap et al. 2016). We incorporate the 2016 county level vote share for democratic candidate Hillary Clinton from the MIT Election Dataset (MIT Election Data and Sciences 2020).

4 Empirical model

To test the impact of natural disasters on climate change beliefs and policy attitudes, we estimate a linear econometric model that includes both county and state-year fixed effects (Woolridge 2010). We include all three natural disasters in a single regression, as opposed to running separate regressions for each disaster. Our linear model specification is similar to other studies (e.g., Kahn and Kotchen 2011).

To test our hypotheses, we implement two empirical specifications. First, we estimate the average effect of natural disasters on climate opinions. To accomplish this, we specify the model as

$$p_{it} = \sum_{d=1}^{3} \beta_{1\{d\}} X_{it\{d\}} + \delta C_{it} + \mu_i + \gamma_{st} + \varepsilon_{it} \tag{1}$$

where p_{it} is the percentage of county i that responded in the affirmative in year t to one of the five survey questions we consider in this study. The term $X_{it\{d\}}$ measures the annual number of disaster type d experienced in county i per year during the 2-year period preceding year t (with the exception of the period preceding 2019, which includes only one year). The coefficients of $\beta_{1\{d\}}$ contain the average effects of natural disaster d on the response to the survey question of interest. Percent change in population and economic changes within a county are controlled for with a vector of population and economic variables for each county and time period, C_{it}, where δ is the vector of coefficients for C_{it}. In addition, C_{it} contains a Clinton vote share trend. Because our political variable does not vary through time, we interact it with a linear time trend. This controls for the fact that conservative and liberal counties may have different trends in climate beliefs. It is important to note that the un-interacted trend, as well as the urban–rural classification of a county, is included within the fixed effect. Therefore, the interpretation of the interaction is the differential trend as a function of the Clinton vote share.

Our models are identified if the occurrence of a natural disaster is not correlated with the error term. This includes any county-level unobservables, such as static political factors, geographic features, and other characteristics, which are difficult to capture in a national-scale study such as this. Since these unobservables may be trending over time, just as natural disasters are, we must control for them. To control for these unobserved factors, we include county (μ_i) and state-year fixed effects (γ_{st}). The latter control for regional political shifts as well as historical adaptation to natural disasters at the state level. The error term is ε_{it}. We cluster our standard errors at the county level. As an exploration of the mechanisms behind our analysis and as a robustness check, we also report a model without time-varying controls in Appendix section A.1. The results from this model reveal qualitatively similar marginal effects of natural disasters compared to the primary specification that includes the control variables.

Our second model tests whether the effect of natural disasters is moderated by a county's historical experience with the natural disasters. To test for this heterogeneity, we specify the model as

$$p_{it} = \sum_{d=1}^{3} \beta_{1\{d\}} X_{it\{d\}} + \beta_{2\{d\}} X_{it\{d\}} \times H_{id} + \delta C_{it} + \mu_i + \gamma_{st} + \varepsilon_{it}. \tag{2}$$

We interact the rate that county i experienced a natural disaster with the historical annual rate of natural disasters, H_{id} for each county and disaster type. The marginal effect of a natural disaster on county-level public opinion in Eq. 2 is given by $\beta_1 + \beta_2 H_{id}$ where H_{id} is the historic rate of a given natural disaster for a given county. Our hypothesis is that β_1 is positive, while β_2 is negative, leading to a smaller marginal effect when a disaster historically has been common in a county. This hypothesis is based on whether individuals who experience more natural disasters in their county may not think an additional natural disaster is unusual; however, an individual who experiences a natural disaster in a county with historically few may interpret it as an information that the climate is changing.

Because the county-level data are modeled from survey responses, there is potential for measurement error biasing our model results. Sparsely populated counties may not have any survey responses to use, and in the data that we use for empirical modeling their levels are estimated entirely by out-of-county survey responses by the Yale PCCC. As more survey responses are added to the database, the quality of the model improves. However, this still represents a potential source of bias if there are more survey responses in urban counties compared to rural counties. Our inclusion of county-fixed effects controls for factors such as rural classification that might impact the probability of being sampled. The state-year fixed effects control for the fact that counties without sufficient responses are modeled using in-state survey responses from that year (Yale PCCC, 2019). Coefficient values from this model can be found in Appendix section A.3.

5 Results

In this section, we report the results of each specification with respect to the five climate change-related questions described above. Overall, we find evidence that hurricanes impact public opinions on climate change. We find no evidence that, conditional on hurricanes, floods have an impact, and evidence that fires have impacts in very limited cases. Furthermore, we find that heterogeneity in the rate of natural disasters in the historic period matters for hurricanes and for fires. In what follows, we present the results of both specifications (Eqs. 1 and 2) in their own subsection.

5.1 Average effects model

We begin by addressing the average effects model (Eq. 1) which reveals the effect that hurricanes, fires, and floods have on beliefs and policy attitudes regarding climate change. Table 3 demonstrates that of the three natural disasters, only hurricanes have statistically significant average effects. We find no evidence that either fires or floods change the proportion of a county that believes in climate change on average.

Hurricanes have a statistically significant effect on several survey questions we consider. We see that the average effect of a hurricane on the percentage of individuals in a county that believe climate change is happening is about 0.252. That means, on average, the occurrence of a hurricane increases the number of people who believe climate change is happening by 0.252 percentage points. It has a slightly higher impact on the proportion of people within a county that believe climate change is human caused (0.199 percentage points); however, the impact on the proportion that believe climate change is caused by human activity is statistically insignificant.

Hurricanes also have statistically significant impacts on the percent of a county that supports funding research into renewable energy (0.174 percentage points), supporting renewable portfolio standards (0.231 percentage points) and setting limits on CO_2 emissions (0.300 percentage points).

The results also reveal that percent change in population, median household income, and the unemployment rate are associated with climate change beliefs. We find that a 1 percentage point increase in the unemployment rate is associated with a 0.152 percentage point decline in the number of people who believe climate change is happening. Interestingly, this is close to the magnitude as the impact of a hurricane. Previous studies (e.g., Kahn and Kotchen 2011) found that a 1 percentage point increase in unemployment

Table 3 Average effects of extreme events on climate beliefs and policy support

	Dependent variables				
	Happening?	Human caused?	Fund renewables?	Support RPS?	$CO_2 limits?$
	(1)	(2)	(3)	(4)	(5)
Hurricane	0.252	0.199	0.174***	0.231*	0.300
	(0.138)	(0.145)	(0.085)	(0.135)	(0.185)
Fire	–0.047	–0.045	–0.045	–0.033	0.001
	(0.065)	(0.070)	(0.041)	(0.061)	(0.090)
Flood	–0.088	–0.028	–0.005	–0.051	–0.067
	(0.067)	(0.060)	(0.033)	(0.055)	(0.079)
Population %Δ	0.003	0.006	0.002	0.003	0.008***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Median household income ($1,000)	0.026**	0.007	–0.032***	–0.005	0.014
	(0.012)	(0.013)	(0.009)	(0.012)	(0.018)
Unemployment	–0.152***	–0.055	–0.160***	–0.232***	–0.134*
	(0.049)	(0.053)	(0.030)	(0.049)	(0.070)
Clinton vote share trend	–1.862***	–1.615***	0.789***	1.715***	2.169***
	(0.108)	(0.108)	(0.049)	(0.063)	(0.103)
County-fixed effects?	Yes	Yes	Yes	Yes	Yes
State-year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observation	11,732	11,732	11,732	11,732	11,732
R^2	0.938	0.914	0.950	0.904	0.907
Adjusted R^2	0.915	0.881	0.931	0.867	0.872
Residual std. error ($df=8512$)	1.764	1.832	1.037	1.692	2.542

*$p<0.1$; **$p<0.05$; ***$p<0.01$

decreases the likelihood an individual believes climate change is happening by 3.3 percentage points, which is an order of magnitude larger than the effect we observe. This difference could occur because our analysis uses more recent data, and so, opinions may have solidified to a greater extent. It may also be due to the higher resolution spatial controls (e.g., county-fixed effects as opposed to state fixed effects) that we use.

We do not detect an effect of the percent change in population for all but one of the questions we consider. We find that a 1% increase in population increases the proportion of individuals that support CO_2 limits by 0.008 percentage points. Median household incomes have small but positive correlated with climate change beliefs and support for limits on CO_2 emissions. Interestingly, income has a negative correlation with support for funding renewable energy research. This could occur if higher income respondents expect to pay a larger share of the funding for renewable energy research. Our results also support previous research that finds a strong connection between political ideology and beliefs regarding climate change. In counties with a higher Clinton vote share, beliefs related to climate change and support for associated policy actions are increasing at a faster rate over time.

As a robustness check, we also estimate the average effects model for each natural disaster separately. We do not find that excluding all but one natural disaster from our models makes a substantial difference with respect to the magnitudes of our coefficients, or with respect to our qualitative results. These results can be found in Appendix section A.4. In
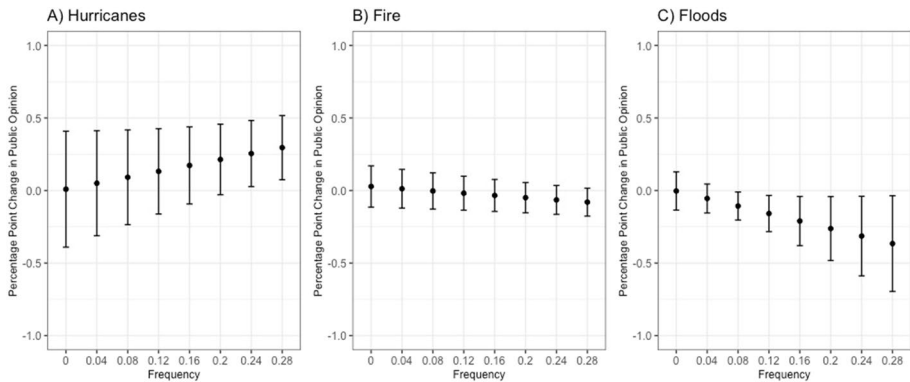
Fig. 2 The effect of hurricanes (Panel **A**), fire, (Panel **B**), and floods (Panel **C**) on the proportion of a county that believes climate change is happening as a function of historic fire frequency. Intervals around the point estimate represent a 90% confidence interval

addition, we recognize that the results may be influenced by the selection of a 2-year treatment window for the 2014, 2016, and 2018 surveys. To investigate whether this is the case, we run the average effects model with a 1-year treatment window instead. We find that the magnitudes of the effects of hurricanes diminish slightly, but that our qualitative results remain the same. These results can be found in Appendix section A.5.

5.2 Heterogeneous effects model

We are also interested in the heterogeneity in impacts as a function of the historic frequency of each event. The full table of regression results is presented in Appendix Table 5 of the appendix, and we use the regression results to generate Fig. 2. The x-axis of Fig. 2 is scaled so that it includes both the mean and 3rd quartile of historic frequencies for each disaster. The effect of a hurricane is estimated to increase with the historic rate of hurricanes (see Fig. 2 Panel A). This implies that counties that have a history of hurricanes experience a larger impact than those that do not, although it does not appear that the marginal effects in the lowest and highest frequency counties are significantly different. This could be because counties with a history of hurricanes have more to lose from an increase in their frequency. A relationship between the beliefs and economic damages may therefore be driving this result. Alternatively, coastal counties with a history of hurricanes may have experienced recent storms with higher degrees of storm severity or are impacted more by the accumulation of hurricane events over time. Investigating the role of economic damages and storm severity would be an interesting area for future research (Davenport et al. 2021).

Conditional on our controls and fixed effects, we find that fire does not have a statistically significant effect. However, at high levels of historic frequency, flooding may actually have a negative effect on the proportion of individuals within a county that believe that climate change is happening, as demonstrated in Fig. 2, Panel C.

The effect may also be different for storms of different magnitudes. However, including magnitudes in the model may result in endogeneity concerns. We test whether there is an effect of magnitudes—measured both in terms of lives lost and property damages—in

Appendix section A.6. These results suggest that the magnitudes of specific natural disasters may influence the extent to which the disasters change climate change beliefs.

6 Conclusion

This paper addresses the impacts of natural disasters on public beliefs regarding several climate change-related issues and policies. Using a panel dataset of county-level public opinions on climate change, we identify the impact of hurricanes, floods, and wildfires on climate change beliefs and policy attitudes. Our results show that hurricanes have a statistically significant average effect on beliefs. When considering heterogeneity, the impact of hurricanes becomes larger when the historic hurricane frequency is higher.

We also revisit observations in the literature with respect to how macroeconomic variables influence opinions. A previous study (Kahn and Kotchen 2011) reports that the percent of a state's population that believes climate change is happening changes by 3.3% for every 1% drop in unemployment. Our analysis finds this effect to be smaller by an order of magnitude. While Kahn and Kotchen (2011) use state-level unemployment rates (as well as state-level fixed effects), we employ county-level unemployment rates, county-level fixed effects, and state-year fixed effects. Therefore, we account for additional spatial heterogeneity that may be correlated with the state-level unemployment rate. We also reinforce results in the literature that political beliefs have strong effects on opinions regarding climate change and associated policy policies.

The findings of our analysis have important implications for policy regarding climate change. We detect statistically significant impacts of hurricanes on the proportion of a county that believes climate change is happening and that it is human caused. We also estimate an increase in support for government regulation of CO_2. This provides evidence of a process in which climate beliefs and policies can respond as the consequences of climate change become apparent.

The fact that we find statistically significant impacts of natural disasters on public opinions reveals that these events are a source of information that can change prior beliefs at the county level. Furthermore, the effects of natural disasters on opinions regarding CO_2 regulation indicate that as these events become more frequent, the number of individuals who are willing to use government as a tool to effect long-term change is likely to increase. The pace at which this feedback occurs, however, appears to be slow. For example, our results indicate that it would take multiple hurricanes hitting a county to increase the proportion of individuals supporting policies that greenhouse gas emissions by one percentage point. As such, it seems unlikely that natural disasters alone will cause sufficient changes in public opinions to bring about widespread acceptance of climate change regulations.

There are several reasons why changes in climate change beliefs following a natural disaster could be a slow process. For instance, individuals may have access to a wide range of information sources that could make the signal noisy (Feldman et al. 2012). The top priority following a natural disaster for those affected is safety, followed by other necessities. The most immediate actions required to combat the disaster take precedent, both for individuals and governments, over long-term concerns such as climate change.

There are several additional research questions that arise from this study. The incidence of the natural disasters that we study often requires government assistance. The effects of government programs on public opinions may influence confidence in other policies such as CO_2 regulation. There is also room to address the importance of a disaster's economic impact in influencing beliefs and attitudes.

Additional studies could examine how disasters impact communities of different political attitudes and economic profiles. For instance, an examination of how heterogenous political attitudes affect a county's response to natural disasters. There may be several mechanisms that influence how political opinions shape individual responses to new information, including ideological stances on government intervention as well as climate change itself. Another area of future research could utilize data such as the hurricane rating system in order to establish whether hurricanes of greater intensity have greater impacts on opinions and preferences.

There are many determinants which contribute to the formation of beliefs, especially those opinions which inform voting behavior and political support. Focusing on climate change, we show that natural disasters, particularly hurricanes, are a determinant of public opinions regarding the issue. We show that not only do hurricanes influence the proportion of people who believe climate change is happening and is caused by human activity, but that they also change the proportion that supports regulating CO_2 emissions.

Appendix 1 Survey questions

What follows are reproductions of the text used in the Yale Climate Opinions survey question used in this study (Yale PCCC, 2019).

Question 1:

Global warming is happening

Recently, you may have noticed that *global warming* has been getting some attention in the news. Global warming refers to the idea that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result. What do you think: Do you think that global warming is happening?

- Yes
- No
- Do not know

Question 2:

Global warming is caused mostly by human activities

Assuming global warming is happening, do you think it is… ?

- Caused mostly by human activities
- Caused mostly by natural changes in the environment
- Other
- None of the above because global warming is not happening

Question 3:

Fund research into renewable energy sources

How much do you support or oppose the following policies?

Fund more research into renewable energy sources, such as solar and wind power.

- Strongly support
- Somewhat support
- Somewhat oppose
- Strongly oppose

Question 4:

Require utilities to produce 20% electricity from renewable sources

How much do you support or oppose the following policies?

Require electric utilities to produce at least 20% of their electricity from wind, solar, or other renewable energy sources, even if it costs the average household an extra $100 a year.

- Strongly support
- Somewhat support
- Somewhat oppose
- Strongly oppose

Question 5:

Set strict CO_2 limits on existing coal-fired power plants

How much do you support or oppose the following policy?

Set strict carbon dioxide emission limits on existing coal-fired power plants to reduce global warming and improve public health. Power plants would have to reduce their emissions and/or invest in renewable energy and energy efficiency. The cost of electricity to consumers and companies would likely increase.

- Strongly support
- Somewhat support
- Somewhat oppose
- Strongly oppose

Appendix 2 Excluding controls

As a robustness check, we report a model that excludes time-varying controls, and only includes fixed effects. Natural disasters may have secondary impacts on climate opinions through population and economic variables. For instance, if a natural disaster changes the population level within a county, and the population level itself affects climate opinions, then the natural disaster will have a secondary impact through changes in the population level. If this effect is substantial, then a model that includes these population variables will underreport the full effect of natural disasters.

In order to investigate whether these secondary effects are substantial, we estimate the average effects model while excluding total population, median income, and the unemployment rate. The results are reported in Table 4.

We observe a small difference between the results in Table 4 and those found in Table 3 of the main text. For each survey question, we find that the effect of hurricanes is larger with the exclusion of the population, economic, and political control variables. This indicates that the indirect effects from one or more of these three variables may partially reinforce the direct effect of hurricanes on opinions. We also find that hurricanes now have a statistically significant effect on whether individuals believe climate change is caused by human activity.

Appendix 3 Regression results for heterogeneity model

Below we present the regression results for Eq. 2. These are used to create Fig. 2 in the main text (Table 5).

Table 4 Average effects model, excluding time-varying controls

	Dependent variables				
	Happening?	Human caused?	Fund renewables?	Support RPS?	$CO_2 limits?$
	(1)	(2)	(3)	(4)	(5)
Hurricane	0.366**	0.297*	0.232**	0.344**	0.433*
	(0.158)	(0.161)	(0.091)	(0.151)	(0.223)
Fire	–0.045	–0.042	–0.045	–0.032	0.004
	(0.092)	(0.094)	(0.053)	(0.088)	(0.130)
Flood	–0.088	–0.033	–0.008	–0.040	–0.068
	(0.072)	(0.073)	(0.041)	(0.069)	(0.101)
County-fixed effects	Yes	Yes	Yes	Yes	Yes
State-year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observation	11,732	11,732	11,732	11,732	11,732
R^2	0.931	0.907	0.946	0.894	0.901
Adjusted R^2	0.905	0.872	0.926	0.853	0.863
Residual std. error ($df = 8516$)	1.863	1.901	1.071	1.783	2.635

*$p < 0.1$;**$p < 0.05$; ***$p < 0.01$

Hurricanes also have statistically significant impacts on the percent of a county that sup-
ports funding research into renewable energy (0.174 percentage points), supporting renew-
able portfolio standards (0.231 percentage points) and setting limits on CO_2 emissions
(0.300 percentage points).

Appendix 4 Single disaster models

In this section, we report three tables in which we examine one natural disaster at a time.
First, we examine hurricanes without including fires or floods (Table 6).

Table 5 The heterogeneous impact of climate-related natural disasters on benefits and policy attitudes as a function of historic disaster frequency

	Dependent variables				
	Happening?	Human caused?	Fund renewables?	Support RPS?	$CO_2 limits?$
	(1)	(2)	(3)	(4)	(5)
Hurricane	0.009	–0.097	0.071	0.009*	–0.043
	(0.244)	(0.269)	(0.148)	(0.253)	(0.342)
Hurricane *historic freq	1.023	1.245	0.434	1.001	1.445
	(0.706)	(0.770)	(0.415)	(0.721)	(0.999)
Fire	0.028	–0.025	–0.075	–0.043	0.035
	(0.087)	(0.099)	(0.058)	(0.090)	(0.132)
Fire *historic freq	–0.385***	–0.096	0.159	0.056	–01.69
	(0.187)	(0.221)	(0.158)	(0.281)	(0.318)
Flood	–0.003	0.062	0.045	–0.022	–0.046
	(0.080)	(0.086)	(0.046)	(0.078)	(0.109)
Flood *historic freq	–1.295	–1.383	–0.776*	–0.447	–1.722
	(0.890)	(0.922)	(0.465)	(0.883)	(1.193)
Population %Δ	0.003	0.006	0.002	0.003	0.008***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Median household income ($1,000)	0.026**	0.007	–0.032***	–0.005	0.014
	(0.012)	(0.013)	(0.009)	(0.012)	(0.018)
Unemployment	–0.152***	–0.056	–0.160***	–0.233***	–0.135*
	(0.049)	(0.053)	(0.031)	(0.049)	(0.070)
Clinton vote share trend	–1.863***	–1.615***	0.789***	1.715***	2.170***
	(0.108)	(0.108)	(0.049)	(0.063)	(0.103)
County-fixed effects	Yes	Yes	Yes	Yes	Yes
State-year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observation	11,732	11,732	11,732	11,732	11,732
R^2	0.938	0.914	0.950	0.904	0.907
Adjusted R^2	0.915	0.881	0.931	0.867	0.872
Residual std. error (df=8512)	1.764	1.832	1.037	1.693	2.542

*$p<0.1$; **$p<0.05$; ***$p<0.01$

Next, we examine a model where we consider only fires, without considering hurricanes or floods (Table 7).

Our third model considers only floods without considering hurricanes or fires (Table 8).

The differences we detect are not significantly different from the results found in the main specifications of the paper.

Appendix 5 Change in treatment period

The effects of natural disasters may diminish with time. To test whether our use of a 2-year treatment period is diminishing the impact of natural disasters, we run a version of our average effects model where we use a treatment period of a single year. We change the treatment period to within a year before the survey, excluding disasters that occur between surveys more than a year prior to a given survey. Though we find that the coefficients are different, we do not find evidence that the difference in magnitude is substantial. In fact, we find that the effect diminishes rather than increases (Table 9).

Table 6 Average effects model, only considering hurricane

	Dependent variables				
	Happening	Human caused	Fund renewables	Support RPS	CO_2limits
	(1)	(2)	(3)	(4)	(5)
Hurricane	0.244	0.197	0.174**	0.227*	0.294
	(0.138)	(0.145)	(0.085)	(0.135)	(0.185)
Population %Δ	0.003	0.006	0.003	0.003	0.008***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Median household income ($1,000)	0.026**	0.007	–0.032***	–0.005	0.014
	(0.012)	(0.013)	(0.009)	(0.012)	(0.018)
Unemployment rate (%)	–0.150***	–0.055	–0.160***	–0.231***	–0.133***
	(0.049)	(0.053)	(0.030)	(0.049)	(0.070)
Clinton vote share trend	–1.862***	–1.615***	0.789***	1.716***	2.170***
	(0.108)	(0.108)	(0.063)	(0.103)	(0.147)
County-fixed effects	Yes	Yes	Yes	Yes	Yes
State-year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observation	11,732	11,732	11,732	11,732	11,732
R^2	0.938	0.914	0.950	0.904	0.907
Adjusted R^2	0.915	0.881	0.931	0.867	0.872
Residual std. error ($df = 8514$)	1.764	1.832	1.036	1.692	2.542

$*p < 0.1; **p < 0.05; ***p < 0.01$

Table 7 Average effects model only considering fires

	Dependent variables				
	Happening	Human caused	Fund renewables	Support RPS	CO$_2$limits
	(1)	(2)	(3)	(4)	(5)
Fire	–0.048	–0.046	–0.045	–0.034	–0.0001
	(0.064)	(0.070)	(0.041)	(0.061)	(0.090)
Population %Δ	0.003	0.006	0.002	0.003	0.008***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Median household income ($1,000)	0.026**	0.007	–0.032***	–0.005	0.014
	(0.012)	(0.013)	(0.009)	(0.012)	(0.018)
Unemployment rate (%)	–0.150***	–0.055	–0.161***	–0.231***	–0.133*
	(0.049)	(0.053)	(0.030)	(0.049)	(0.070)
Clinton vote share trend	–1.865***	–1.617***	0.791***	1.718***	2.173***
	(0.108)	(0.108)	(0.063)	(0.103)	(0.147)
County-fixed effects	Yes	Yes	Yes	Yes	Yes
State-year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observation	11,732	11,732	11,732	11,732	11,732
R^2	0.938	0.914	0.950	0.904	0.907
Adjusted R^2	0.915	0.881	0.931	0.867	0.872
Residual std. error (*df*=8514)	1.764	1.832	1.037	1.693	2.542

*$p<0.1$; **$p<0.05$; ***$p<0.01$

Table 8 Average effects model only considering floods

	Dependent variables				
	Happening	Human caused	Fund renewables	Support RPS	CO$_2$limits
	(1)	(2)	(3)	(4)	(5)
Flood	–0.084	–0.025	–0.002	–0.047	–0.062
	(0.057)	(0.060)	(0.033)	(0.055)	(0.079)
Population %Δ	0.003	0.006	0.003	0.003	0.008***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Median household income ($1,000)	0.025**	0.007	–0.032***	–0.005	0.014
	(0.012)	(0.013)	(0.009)	(0.012)	(0.018)
Unemployment (%)	–0.152***	–0.056	–0.161***	–0.232***	–0.135*
	(0.049)	(0.053)	(0.030)	(0.049)	(0.070)
Vote share trend	–1.864***	–1.617***	0.791***	1.718***	2.172***
	(0.108)	(0.108)	(0.063)	(0.103)	(0.147)
County-fixed effects	Yes	Yes	Yes	Yes	Yes
State-year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observation	11,732	11,732	11,732	11,732	11,732
R^2	0.938	0.914	0.950	0.904	0.907
Adjusted R^2	0.915	0.881	0.931	0.867	0.872
Residual std. error (*df*=8514)	1.764	1.832	1.037	1.692	2.542

*$p<0.1$;**$p<0.05$;***$p<0.01$

Table 9 Average effects model with a treatment period that only considers natural disasters in prior year

	Dependent variables					
	Happening	Human caused	Regulate	Fund renewables	Support RPS	CO_2 limits
	(1)	(2)	(3)	(4)	(5)	(6)
Hurricane	0.181*	0.131	0.139*	0.126**	0.181*	0.203
	(0.095)	(0.101)	(0.073)	(0.057)	(0.094)	(0.129)
Fire	−0.047	−0.045	−0.060	−0.044	−0.032	0.001
	(0.065)	(0.070)	(0.056)	(0.041)	(0.061)	(0.090)
Flood	−0.090	−0.029	−0.018	−0.006	−0.053	−0.069
	(0.057)	(0.060)	(0.047)	(0.033)	(0.055)	(0.079)
Population %Δ	0.003	0.006	0.003	0.002	0.003	0.008***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Median household Income ($1,000)	0.026**	0.007	−0.004	−0.032***	−0.005	0.014
	(0.012)	(0.013)	(0.010)	(0.009)	(0.012)	(0.018)
Unemployment rate (%)	−0.151***	−0.055***	−0.089***	−0.160***	−0.231***	−0.133*
	(0.049)	(0.053)	(0.039)	(0.030)	(0.049)	(0.070)
Clinton vote share trend	1.862***	1.615***	1.311***	0.790***	1.716***	2.170***
	(0.108)	(0.108)	(0.083)	(0.063)	(0.103)	(0.147)
County-fixed effects?	Yes	Yes	Yes	Yes	Yes	
State-year fixed effects?	Yes	Yes	Yes	Yes	Yes	
Observation	11,732	11,732	11,732	11,732	11,732	11,732
R^2	0.938	0.914	0.922	0.950	0.904	0.907
Adjusted R^2	0.915	0.881	0.892	0.931	0.867	0.872
Residual std. error (df=8512)	1.764	1.832	1.435	1.036	1.692	2.542

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Appendix 6 The effects of disaster magnitudes on climate opinions

In our manuscript, we include variables indicating whether a particular kind of natural disaster occurred in a county in each treatment period. One concern with this approach is that it does not consider the magnitude of the natural disasters in question. We choose to not include magnitudes in our main specification because of issues of endogeneity. We are concerned that preferences for policies and the magnitude of damages from a given disaster may be influenced by county level unobservables related to the population density, as well as the quantity of built structures within a county within a given period and previous adaptation expenditures that likely influence the overall impact of a natural disaster. Alleviating this endogeneity issue is beyond the scope of this paper; however, we provide some results below that investigate the extent to which disaster magnitudes impact opinions.

One might hypothesize that there is a difference in the effect of natural disasters depending on the degree of impact. To test this hypothesis, we use the NOAA storm events database (NOAA 2021), which contains a record of disaster events between 1950 and 2018. Included in this record are measures of the financial impact of each event. The measure of impact we select is property damage, which is reported in $1,000 s of dollars. This allows us to have a measure of damage that is consistent across the three types of natural disasters that we evaluate. We report some abbreviated summary stats for the NOAA disaster data in Table 10. On average, there are more reports of floods in the dataset than other types of disasters, and these also have the largest expected lives lost, followed by hurricanes. Hurricanes, on the other hand, result in more property damage on average.

We specify the average effects model to account for heterogeneity across storms related to the magnitude of impact.

$$p_{it} = \sum_{d=1}^{3} \left(\beta_{1d} X_{itd} + \beta_{2d} X_{itd} \times M_{itd} \right) + \delta C_{it} + \mu_i + \gamma_{st} + \varepsilon_{it}. \tag{3}$$

In Eq. 3, we interact the magnitude of a given disaster with the occurrence of that disaster. This accomplishes two things. First, it allows us to scale the effect of the natural disaster by the magnitude of the impact. Second, it allows us to include disasters for which the impact magnitudes are not reported. An issue with the NOAA dataset, as well as other datasets such as EM-DAT (CRED 2021), is that the magnitudes of the impacts are sometimes reported as zero, where it is impossible to tell whether the actual number is zero or whether the number was not reported. The results of estimating Equation A.1. are reported in Table 11 for damages measured in terms of lives lost. We also measure damages in terms of property damage, the results of which are found in Table 12.

Table 10 Description of damage data from NOAA				Property damage ($1,000 USD)	
Variable	Number of report	Mean	Max	Mean	Max
Fire	439	0.02	3	30	1000
Flood	5564	0.09	42	110	7500
hurricane	20	0.05	1	975.8	3252

Table 11 The effect of natural disaste damanges, measured in terms of lives lost, on the average

	Dependent variables				
	Happening	Human caused	Fund renewables	Support RPS	CO_2limits
	(1)	(2)	(3)	(4)	(5)
Hurricane	0.660***	0.582**	0.391***	0.739***	0.904***
	(0.246)	(0.262)	(0.146)	(0.250)	(0.340)
Fire	–0.024	–0.043	–0.041	–0.068	–0.041
	(0.118)	(0.128)	(0.066)	(0.124)	(0.179)
Flood	–0.166**	0.153	–0.098**	–0.133*	–0.183*
	(0.077)	(0.080)	(0.044)	(0.078)	(0.105)
Population %Δ	0.301***	0.299***	0.011	0.253***	0.431***
	(0.080)	(0.079)	(0.020)	(0.075)	(0.113)
Median household Income ($1,000)	0.024	–0.003	–0.034***	–0.002	0.017
	(0.017)	(0.017)	(0.010)	(0.017)	(0.025)
Unemployment rate (%)	–0.351***	–0.229***	–0.199***	–0.371***	–0.400***
	(0.062)	(0.065)	(0.037)	(0.062)	(0.090)
Hurricane *lives	0.476***	1.350***	–0.033	–0.573***	0.520***
	(0.130)	(0.137)	(0.068)	(0.118)	(0.154)
Fire*lives:fire	–1.807***	–0.461***	0.026***	–0.663***	–0.670***
	(0.558)	(0.151)	(0.094)	(0.127)	(0.295)
Flood *lives	–1.030	–0.055**	0.013**	–0.035*	–0.039
	(0.023)	(0.022)	(0.006)	(0.018)	(0.028)
County-fixed effects?	Yes	Yes	Yes	Yes	Yes
State-year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observation	9,406	9,406	9,406	9,406	9,406
R^2	0.938	0.904	0.949	0.884	0.895
Adjusted R^2	0.890	0.853	0.922	0.822	0.839
Residual std. error ($df=6156$)	1.978	2.077	1.182	1.961	2.916

*$p<0.1$;**$p<0.05$; ***$p<0.01$

Our results suggest that for hurricanes, their impact on climate change beliefs and support for policy increases as the number of lives lost increases. We see that for fire and floods, this effect is reversed. However, as mentioned above, there may be endogeneity concerns related to using the number of lives lost as an explanatory variable. In addition, the numbers of lives lost reported in the NOAA data are relatively small and do not vary much. We conduct an additional regression where instead of using lives lost, we use a measurement of property damage. The results of this estimation can be found in Table 12

From Table 12, we see that the effect of hurricanes on all opinions and policy preferences remains positive and statistically significant at 1% level. Interestingly, for most survey questions, the more damage a hurricane causes, the smaller the impact it has on opinions. This is likely due to endogeneity issues related to hurricanes occurring in coastal

Table 12 Incorporating property damage into the average effect regression

	Dependent variables				
	Happening	Human caused	Fund renewables	Support RPS	CO_2limits
	(1)	(2)	(3)	(4)	(5)
Hurricane	0.660***	0.577**	0.394***	0.733***	0.906***
	(0.246)	(0.263)	(0.145)	(0.250)	(0.339)
Fire	–0.039	–0.045	–0.037	–0.071	–0.037
	(0.117)	(0.126)	(0.066)	(0.123)	(0.178)
Flood	–0.248***	–0.247***	–0.134***	–0.187**	–0.291**
	(0.084)	(0.086)	(0.047)	(0.085)	(0.114)
Population %Δ	0.285***	0.271***	0.003	0.235***	0.410***
	(0.073)	(0.076)	(0.021)	(0.068)	(0.102)
Median household income ($1,000)	0.024	-0.001	–0.034***	–0.003	0.018
	(0.017)	(0.017)	(0.010)	(0.016)	(0.025)
Unemployment rate (%)	–0.351***	–0.229***	–0.199***	–0.370***	–0.399***
	(0.062)	(0.065)	(0.037)	(0.062)	(0.090)
Hurricane *damages	–0.001***	0.001	–0.001	–0.001***	0.0.02**
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.001)
Fire*damage	0.002	0.003***	–0.001	0.001	–0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Flood *damage	0.0004***	0.0005***	0.002**	0.0003*	–0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
County-fixed effects?	Yes	Yes	Yes	Yes	Yes
State-year fixed effects?	Yes	Yes	Yes	Yes	Yes
Observation	9,406	9,406	9,406	9,406	9,406
R^2	0.928	0.904	0.949	0.884	0.895
Adjusted R^2	0.890	0.853	0.922	0.822	0.839
Residual std. error ($df=6156$)	1.978	2.077	1.181	1.961	2.915

*$p<0.1$;**$p<0.05$; ***$p<0.01$

zones with lots of structures. Though the effects of fires on opinions are not statistically significant, as fires become more damaging, the effect becomes stronger on opinions regarding whether climate change is caused by human activity. We detect a mixed impact of floods on opinions and policy preferences when including property damage. Though we detect that floods have a negative impact, this is offset by the impact of flood damages on opinions, so that the effect of floods on the outcome variable on average is not different from zero (Table 3 manuscript). As floods become more damaging, the effect on opinions becomes more positive. This result holds across all five questions considered in this study.

In general, we detect that the magnitudes of natural disasters, measured in terms of lives lost and property damages, impact how natural disasters influence climate change beliefs and policy support. However, we caution that the results may be biased due to endogeneity concerns, which are not addressed in this analysis but is an exciting area of future study.

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